FY 2005

NCDOT

Research Proposal

Subcommittee: Structures

Project Title: **Fuzzy Neural Network Models for Geotechnical Problems**

Submittal Date: April 16, 2004

Organization: North Carolina State University

Researcher:
M. S. Rahman
Department of Civil Engg.
Campus Box 7908
Raleigh, NC 27695-7908

____

Telephone: (919) 515-7633 Fax: (919) 515-7908
Email: rahman@eos.ncsu.edu

Fuzzy Neural Network Models for Geotechnical Problems

PROJECT SUMMARY

Uncertainty, imprecision, complexity, and non-linearity are inherently associated with many problems in geotechnical engineering. The conventional modeling of the underlying systems, tend to become quite intractable and very difficult requiring evaluation of large number of system parameters. Recently an alternative approach to modeling has emerged under the rubric of 'soft computing' with 'neural network' and 'fuzzy logic' as its main constituents. These are observational models developed on the basis of available set of data. The general nature of geotechnical problems and the consequent role engineering judgments play in their treatment, make them ideally amenable to modeling through these emerging methods of modeling.

Several years ago the PI made a presentation during a DOT meeting at Asheville, NC in which the usefulness of neural network modeling for Geotechnical problems was demonstrated. This was very well received by the practicing DOT engineers. Later during a meeting with Mr. Mohammed Mulla, Mr. K J Kim, Mr. John Ledbetter, and several other NCDOT engineers, the PI suggested that neural network based modeling has significant potential for reliable prediction for several problems encountered by NCDOT engineers. Subsequently the PI in consultation with Mr. Mulla and Mr. Kim developed the research idea and submitted a pre-proposal for this study (*Research Idea ST-01* in the NCDOT FY-2004 *Call for New Research Idea).* A proposal was submitted which was received quite favorably but could not be funded. Again this year, we followed the same course and on the recommendation and incorporating the modifications suggested by Roger Rochelle on behalf of Structures Research Subcommittee, this final proposal is being submitted for FY-2005.

The main objective of the proposed research is to: (i) develop a general framework and a computational toolbox for development of fuzzy neural network models to geotechnical problems, and (ii) to develop a fuzzy neural network model for the development of pile driving criteria related to hammer approval.

The following products are expected to result from the proposed study: (a) a general framework and a toolbox for development of fuzzy neural network model for a typical geotechnical problem, and (b) a trained model for the development of pile driving criteria. The model will be implemented in form of user friendly software with a convenient graphical user interface (GUI). A user friendly manual will also be developed. A brief training module will also be provided.

Once this study is completed other specific models can be easily developed for other specific problems. Since this new approach of modeling is based on observational data, and NCDOT has at its disposal good data bases for several problems, it is expected that this study will facilitate the development of specific models for several other problems of interest to NCDOT engineers. These models will be capable of incorporating the accumulated experience of NCDOT engineers. This will also lead to development of organized databases for several significant problems.

TABLE OF CONTENTS

1.0 INTRODUCTION

1.1 Background

Few years ago the PI made a presentation during a DOT meeting at Asheville, NC in which the usefulness of neural network modeling for Geotechnical problems was demonstrated. This was very well received by the practicing DOT engineers. Later during a meeting with Mr. Mohammed Mulla, Mr. K J Kim, Mr. John Ledbetter, and several other NCDOT engineers, the PI suggested that neural network based modeling has significant potential for reliable prediction for several problems encountered by NCDOT engineers. Subsequently the PI in consultation with Mr. Mulla and Mr. Kim developed the research idea and submitted a pre-proposal for this study (*Research Idea ST-01* in the NCDOT FY-2004 *Call for New Research Idea).* This final proposal is based on the pre-proposal incorporating the modifications suggested by Mr. Roger Rochelle on behalf of Structures Research Subcommittee.

1.2 Characteristics of Geotechnical Problems

Uncertainty, imprecision, complexity, and non-linearity are inherently associated with many problems in geotechnical engineering. The general characteristics of geotechnical problems are outlined in the following:

- Most parameters associated with the geotechnical problems must be obtained from in-situ or laboratory testing. Due to the limited number of exploratory borings we can drill and the number of laboratory tests we can perform, only a very small portion of the parameters can be obtained. This introduces many potential sources of error and it is also the major source of uncertainty involved with the geotechnical problems.

- There exists vagueness or imprecision associated with many of the governing variables and their effects on the response of the system. Engineering judgments based on experience, subjectivity, reliance on precedent, and other factors are frequently used deal with this non-statistical uncertainty.

- Soil is different from other materials in that it can simultaneously contain solid, liquid, and gas phases and it is heterogeneous, anisotropic and nonlinear. In order to construct mathematical model, we normally need to introduce certain simplifying assumptions. Nonlinearity of soil behavior produces lots of difficulties in modeling.

- Most of geotechnical problems need to consider a large number of variables that affect the response of the studying systems. Thus, complexity is also an inherent feature of these problems.

1.3 Problem Statement

Because of the above mentioned general characteristics, conventional mathematical modeling of the geotechnical problems tend to become very difficult and often the prediction is quite unreliable. Currently NCDOT is experiencing serious difficulties with many problems: bearing capacities of foundations, driving criteria for piles, settlement analysis etc. As instructed by the research subcommittee, in this study we will focus on the following problem.

Pile Driving Criteria: Hammer approval

NCDOT provides pile driving criteria for the contractor to drive the piles to the required pile bearing capacity for every bridge construction project. Engineers at NCDOT use a wave equation based computer program to generate the pile driving criteria for every project. This work takes up a significant amount of time of the Soils and Foundation Section. Also, timely delivery of the pile driving criteria is very important for the contractor to meet the construction schedule. Sometimes, the contractor needs to replace an approved hammer due to unexpected problems in the middle of pile driving, and it delays the construction because the contractor needs to resubmit their replacement hammer data and wait for new driving criteria. The pile driving criteria furnished by NCDOT to the contractor include the required hammer drops for the proposed hammer and for the design bearing capacity. The criteria also specify the range of hammer stroke and fuel setting, and the maximum blow count the contractor should follow during the pile driving.

There exits an urgent need for the development of a quick, easy and reliable means of developing the pile driving criteria.

1.4 Fuzzy and Neural Network Modeling

General

The essence of modeling is prediction which is obtained by mapping a set of variables in input space to a set of response variables in output space through a model as represented in the figure below.

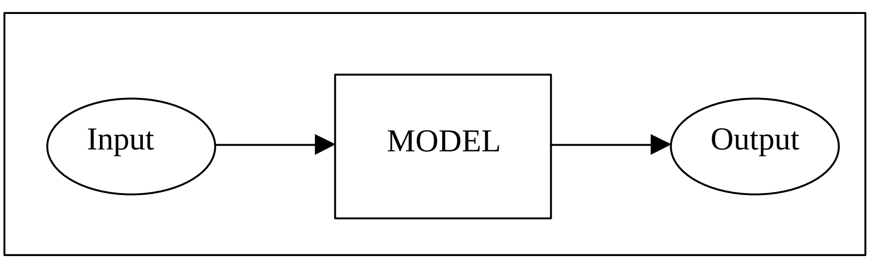

Figure1. An input – output mapping.

In the box representing a model in the above figure, conventionally we place a mathematical model. However, because of the general characteristics of geotechnical problem mentioned earlier, the conventional modeling of the underlying systems, often tend to becomes intractable and very difficult. And with lot of simplifying assumptions made in such models, the resulting predictions are usually not satisfactory as has been the experience of NCDOT especially with respect to the problem of pile driving criteria for hammer approval under consideration.

Recently an alternative approach to modeling has emerged under the rubric of 'soft computing' with 'neural network' and 'fuzzy logic' as its main constituents. These are 'observational models' developed on the basis of available set of data representing a mapping between input and output variables. The applications of these new approaches to modeling are already underway [see section 8.1, 1-5, and section 8.2, 1-10]. The general nature of geotechnical problems and consequent role engineering judgments play in their treatment, make them ideally amenable to this new approach of modeling. The development of these models however requires a set of data. Fortunately, for many problems NCDOT has over the past several years accumulated reasonably large set of data for several problems including those for pile driving criteria.

Fuzzy System

There exists non-statistical uncertainty (in the form of 'vagueness' or 'imprecision') associated with many variables. These variables and their influences on the system are defined in linguistic terms. This form of uncertainty can be handled in a rational framework of 'fuzzy set theory'. It can be said that probability deals with statistical uncertainty, whereas fuzziness has been introduced as a means of representing and manipulating non-statistical uncertainty. In contrast to a classical set, a fuzzy set is a set without a crisp boundary. The transition from 'belong to a set' to 'not belong to a set' is gradual, and this transition is characterized by membership functions that give fuzzy sets flexibility in modeling commonly used linguistic expressions, such as 'relative density of the soil is high'. These linguistic terms represented by fuzzy numbers A, B, C, D, and E are defined by the membership functions shown in Figure 2.

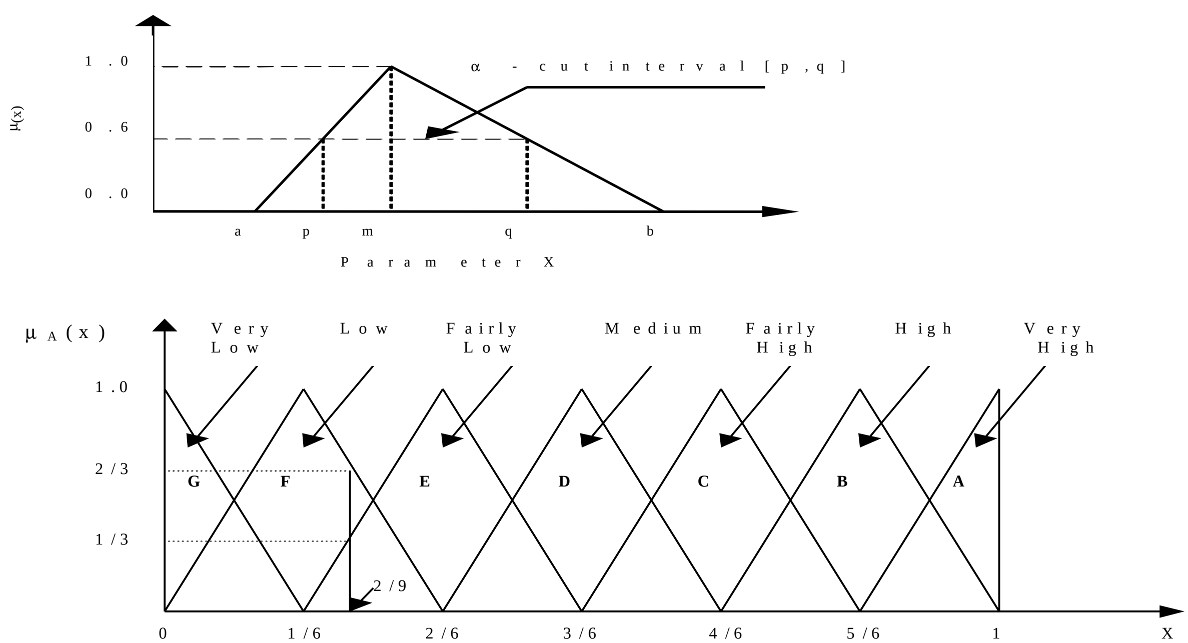

Figure 2. Membership Function and Definition of Linguistic Grades

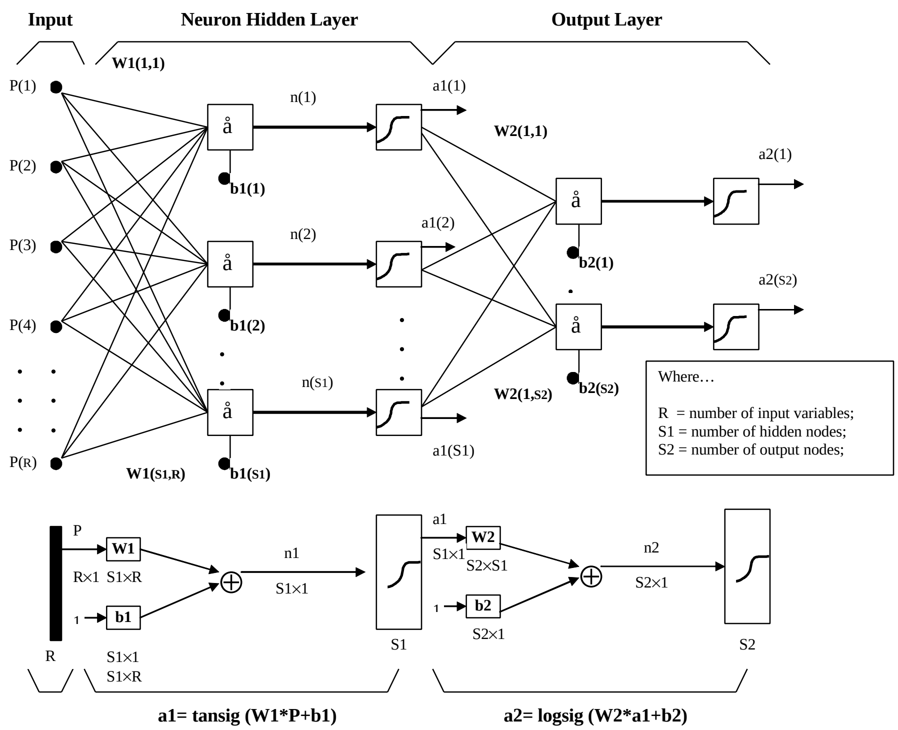

Figure 3. A Typical Artificial Neural Network Architecture

Artificial Neural Network Model

An Artificial Neural Network is a "computational mechanism able to acquire, represent, and compute a mapping from multivariate space of information to another, given a set of data representing that mapping". A neural network consists of a large set of interconnected neurons (i.e. processing units). These neurons are arranged in many layers and interact with each other through weighted connections. Neural networks are trained by the presentation of a set of examples of associated input and output (target) values. The hidden and output layer neurons process their inputs by multiplying each of their inputs by the corresponding weights, summing the product, and then processing the sum using a nonlinear transfer function to produce a result. The S-shaped sigmoid function is commonly used as the transfer function. The neural-network "learns" by adjusting the weights between the neurons in response to the errors between actual output values and target output values. At the end of this training phase, the neural network represents a model, which should be able to predict a target value given the input value.

Artificial neural network models are adaptive and capable of generalization. They can handle imperfect or incomplete data, and can capture nonlinear and complex interactions among variables of a system. Because of these strengths, the artificial neural network method is emerging as a powerful tool for modeling.

A typical back-propagation artificial neural network is shown in Figure 3. A network can have several layers. The outputs of each intermediate layer are the inputs to the following layer. Each layer has a weight matrix ***W***, a bias vector ***b***, and an output vector ***a***. Each element of the input vector ***p*** is connected to each neuron input through the weight matrix ***W***. The *i*th neuron has a summer that gathers its weighted inputs and bias to form its own scalar output *n (i)*. The various *n(i)* taken together form an *S*-element vector ***n***. Finally, the neuron layer outputs form a column vector ***a***. The layers of a multilayer network play different roles. The layer that produces the network output is called an *output layer*. The layer that gets the inputs is called *input layer*. All other layers are called *hidden layers*. It is common for the number of inputs to a layer be different from the number of neurons. The network shown in Figure 2 has *R* inputs (*R* neurons in the input layer), *S1* neurons in the hidden layer, and *S2* neurons in the output layer. The number of hidden layers can be varied based on the application. A constant input value of 1 is fed to the biases for each neuron.

Integrated Fuzzy and Artificial Neural Network Models

Fuzzy systems and neural networks are both model-free numerical estimators. They share the ability to improve the predictive capability of a system working in uncertain, imprecise, and noisy environments. Fuzzy logic and neural networks are complementary technologies. In order to utilize strengths of both, fuzzy logic and neural networks may be combined into an integrated system. The integrated system then has the advantage of both neural networks (e.g. learning abilities, optimization abilities, and connectionist structure) and fuzzy logic (e.g. human-like if-then rules, and ease of incorporating expert knowledge available in linguistic terms).

One approach to integrate fuzzy logic and a neural network is to simply fuzzify some of the neural network system parameters and retain the basic properties and architectures of the neural network model. In such models, a crisp neuron becomes fuzzy and response of the neuron to its lower-layer activation signal is of a fuzzy relation. The learning mechanisms and interpretation capability of the neural network system is enhanced by fuzzy representation of the knowledge domain. The neural network architecture remains unchanged while the only change is in the weights, which connect low-level to high-level neurons. In order for a neural network to handle the fuzzy inputs, the network parameters, i.e., the weights that connected each neuron and the bias in each layer are fuzzified based on a two-stage training mechanism.

Another approach to combine fuzzy system and neural network modeling is to use a fuzzy inference system (FIS) for the process of mapping. Fuzzy inference is the process that maps a set of input variables to output variables through a set of fuzzy rules. These rules are obtained using the available data set in the framework of some standard form. The first step for a fuzzy inference system is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. In this approach of integration, FIS is combined with a back propagation algorithm on the compiled data set, to develop an Adaptive Neuro-Fuzzy Inference Model (ANFIM) which can then be used for prediction.

There may be several other approaches available to integrate fuzzy system and neural network modeling. The overall form of these approaches will be dictated by the nature of the problem the data type available, and the kind of prediction needed.

2. OBJECTIVE

The main objective of the proposed research is to: (i) develop a general framework and a computational toolbox for development of fuzzy neural network models to geotechnical problems, and (ii) to develop an integrated fuzzy neural network model for the development of pile driving criteria related to hammer approval. The data available with NCDOT will be collected, categorized and organized into data bases. The fuzzy neural network model will be trained using these data bases to make prediction for the development of pile driving criteria for a given set of conditions.

3. RESEARCH PLAN

The proposed work scope will include formulation of a general framework and computational tool box, data compilation, and development of a fuzzy neural network model for pile driving criteria. The research plan will consist of the following tasks:

<u>Task 1: Literature Review</u>

The field of fuzzy and neural network modeling has been evolving at a very rapid rate. In recent years there has been lot of progress made in both the development of the basic theories and its applications in solving decision making, modeling, and control problems. These emerging tools have been applied to many civil engineering problems including several geotechnical problems. In order to initiate the proposed study there is a need for a rather comprehensive literature review of both the developments in basic theories and recent applications. In this task such a review will be carried out in order to develop a clear perspective of the state -of-the art-and practice. Special focus will be on those studies in which fuzzy and neural network modeling have been integrated.

<u>Task 2: Data Collection and Compilation</u>

NCDOT has generated numerous pile driving criteria (well over 1000) during the last 20 years or so. It also maintains the actual pile driving data (i.e. actual blow count for the design bearing with the furnished driving criteria) for many of the construction projects completed or under construction. These data will be collected, categorized, compiled and organized in a systematic data base. All the information available from each construction project including the hammer type, pile type, pile design load, soil types and other geologic characteristics of each site will be reviewed and compiled in the database.

<u>Task 3: The Development of General Fuzzy Neural Network Model</u>

First of all, based on a literature review, we will choose the best way of developing an integrated fuzzy neural network model. We will then develop a tool box of sufficiently general capability to make prediction for typical geotechnical problem. This general model will allow the user to define : the number of input and output variables, type (fuzzy or non-fuzzy) variables, number of hidden variables, number of fuzzy rules, types of membership functions for fuzzy variables, and other system parameters. This model will be of general enough in form of a shell within which specific models can be developed for a typical geotechnical problem.

Task 4: Fuzzy Neural Network Model for Pile Driving Criteria

Using a process of random selection, the data set compiled in Task 2 will be divided into two categories: training data and testing data. The fuzzy neural network model will be developed using the training data set. While training this model, a systematic study will be made to evaluate the relative importance of all the input variables. The trained model will then be tested for its prediction (of number of hammer drops, and other target variables) for the testing data. The final product of this task will be a trained fuzzy neural network model implemented in a computer software with convenient graphical user interface.

Task 5: Reporting

The results from the proposed study will be reported quarterly. At the end of the duration a final report along with all the documentation of the models and the computer programs will also be submitted.

Task 6: Training and Publication

Immediately after the proposed study is complete and the final report is accepted by the NCDOT, the principal investigator will offer a training course for all the NCDOT personnel who will use the developed models. A user friendly manual will also be developed. A brief training module will also be provided. Also, the research results will be submitted to the nationally recognized professional organizations for publication.

4. ANTICIPATED RESULTS AND SIGNIFICANCE

The following products are expected to result from the proposed study: (a) a general framework and a toolbox for development of fuzzy neural network model for a typical geotechnical problem, and (b) a trained model for the development of pile driving criteria. The model will be implemented in form of user friendly software with a convenient graphical user interface (GUI). A user friendly manual will also be developed. A brief training module will also be provided.

The trained fuzzy neural network model for hammer approval will provide pile driving criteria for a proposed hammer and for the design load without performing the wave equation analysis by an engineer. This model will not require advanced knowledge or experience in soil mechanics and geotechnical engineering to perform the rigorous wave equation analysis. It will be able to provide the driving criteria much quicker than the current practice. The model will be available to the NCDOT construction personnel at the project site, and the construction personnel should be able to use the model to generate the pile driving criteria. It will save the NCDOT engineers' time and prevent construction delay or claim due to the required turn-around time for hammer approval and developing pile driving criteria.

Once this study is completed other specific models can be easily developed for other specific problems. Since this new approach of modeling is based on observational data, and NCDOT has at its disposal good data bases for several problems, it is expected that this study will facilitate the development of specific models for several other problems of interest to NCDOT engineers. These models will be capable of incorporating the accumulated experience of NCDOT engineers. This will also lead to development of organized databases for several significant problems.

5. RESOURCES FROM NCDOT

The scope of the proposed work and the model to be developed will rely on the data available at NCDOT on pile driving and hammer approval. The PI and his students will need access to these data along with the useful guidance from the NCDOT engineers familiar with those data.

6. DURATION AND TIME REQUIREMENTS

Table 1 below shows the proposed timeline for the various tasks in this project. The extent of the experimental program requires 18 months of rigorous analysis and testing to achieve the objectives of the project.

Table 1. Proposed Timeline

Task	**Year**	2004-05				2005-06	
	Quarter	1	2	3	4	1	2
1. Literature Review							
2. Data Collection and Compilation							
3. General Fuzzy and Neural Network Modeling							
4. Fuzzy Neural Network for Pile Driving Criteria							
Reporting							
6. Training and Publication							

7. QUALIFICATIONS AND ACCOMPLISHMENTS OF THE PI

M. S. Rahman is Associate Professor of Civil Engineering at North Carolina State University specializing in Geotechnical Engineering. He has extensive experience in modeling and computing for geotechnical engineering. Dr. Rahman has recently developed and published fuzzy and neural network models for several important geotechnical problems.

8. PUBLICATIONS

8.1 Cited Publications by PI

1. Rahman, M.S. and Wang, J., (2002). Adaptive neural fuzzy inference model for earthquake induced horizontal ground displacement. Submitted to Soil Dynamics and Earthquake Engineering.

2. Rahman, M.S., and Wang, J. (2002). Fuzzy neural network models for liquefaction prediction. To appear in Soil Dynamics and Earthquake Engineering (Accepted, May 2002).

3. Rahman, M.S., Wang, J., Deng, W., & Carter, J.P. (2001). A neural network model for the uplift capacity of suction caissons. Computer and Geotechnics 28(4): 269-287.

4. Wang, J., & Rahman, M. S. (1999). A neural network model for liquefaction-induced horizontal ground displacement, Soil Dynamics and Earthquake Engineering 18: 555-568.

5. Rahman, M. S. & El Zahaby, K. M. (1997). Probabilistic liquefaction risk analysis including fuzzy variables. Soil Dynamics and Earthquake Engineering 16(1): 63-79.

8.2 Cited Publications by Others

1. Romo MP (1999). Earthquake geotechnical engineering and artificial neural networks. Fourth Casagrande lecture, XI Pan American Conference on Soil Mechanics and Geotechnical Engineering, Brazil.

2. Chen, JW. & Chen CY (1997). A fuzzy methodology for evaluation of the liquefaction potential. Microcompuers in Civil Engineering. 12: 193-204.

3. Agrawal G., Chameau, JLA., & Bourdeau, PL (1997). Assessing the liquefaction susceptibility at a site based on information from penetration testing. In: Kartam N., Flood, I., and Garret, J. H. (eds), Artificial Neural Networks for Civil engineers: Fundamentals and Applications, American Society of Civil Engineers, New York, 185-214.

4. El Zahaby, KM. & Rahman, MS (1996). Non-statistical uncertainties in liquefaction risk assessment, Proceedings of the conference on Uncertainty in Geologic Environment; From Theory to Practice, ASCE, Geotechnical Special Publication, 58:1068-1082.

5. Najjar, YM. & Basheer IA (1996). A neural network approach for site characterization and uncertainty Problems, Proceedings of the conference on Uncertainty in Geologic environment; From Theory to Practice, ASCE, Geotechnical Special Publication, 58:134-148.

6. Ni, SH, Lu, PC & Juang, CH (1996). A fuzzy neural network approach to evaluation of slope failure potential, Microcomputers in Civil Engineering, 11: 59-66.

7. Ghaboussi, J., Garret, JH. & Wu, X (1991). Knowledge based modeling of material behavior with neural networks. Journal of Engineering Mechanics Division, ASCE, 117, 2: 132-153.

8. Goh, ATC (1994). Seismic liquefaction potential assessed by neural networks, Journal of Geotechnical Engineering Division, ASCE, 120, 9: 1467-1481.

9. Goh, ATC (1996). Neural network modeling of CPT seismic liquefaction data, Journal of Geotechnical Engineering Division, ASCE 122:170-73.

10. Juang, CH., Huang, XH. & Elton, DJ. (1992). Modeling and analysis of non-random uncertainties - fuzzy set approach, 16:335-350.